Exhibit 4
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First-Price RPO

[redacted]

11/30/2020

Outline

1. Theory
2. Model Design
3. Experiment Design
4. Current Status

Theory - bidding in second-price auctions

- Utility = (value - runner_up_bid) when wins; 0 when loses.
- Bidding true value is the optimal strategy in second price auctions.
    - Link

Theory - bidding in first-price auctions

- Utility = (value - bid) when wins; 0 when loses.
- Assuming 2 bidders with IID uniform value distribution in [0, 1], the Nash equilibrium is each bidder bids half of their true value, i.e. bidder 1 bids v1/2, and bidder 2 bids v2/2
  - Link
  - Can be generalized to n bidders with symmetric setting.
  - Seller's expected revenue is ⅓.
    - E(max(b1, b2)) = 0.5 * E(max(v1, v2))
  - Revenue equivalence with second-price auctions, under symmetric setting.

Theory - bidding in first price auctions with reserve price

- 2 bidders with IID uniform value distribution in [0, 1] in a first-price auction with reserve price r. The Nash equilibrium is each bidder bids B(v, r) = v/2 + r^2/(2v) when v > r; 0 otherwise.
  - A more generalized result can be found here.
  - We can see bidders bid higher given reserve price.
  - Optimal reserve price maximizes seller's revenue: E(max(B(v1, r), B(v2, r))).
    - Optimal reserve price in this case is ½, which yields **5/12** publisher revenue. Note that this is larger than the result (1/3) we obtained without reserve price.
- Theory vs Reality
  - Asymmetric value distributions.
  - Bidders' bids are correlated.

Model Design

1. For each DynamicPriceKey, generate a reserve price.
2. Two algorithms so far:
    a. Quantile based reserve, e.g. 20th percentile of bid distribution.
        i. Easy to interpret.
        ii. Empirical-based. No academic theory regarding whether it's optimal or not.
    b. True value estimation based reserve (doc1, doc2).
        i. Under linear shading assumptions (i.e. b = alpha * v for some constant alpha), we can estimate the shading factor alpha (and therefore true value v) given a bidder's bid distribution and HOB distribution.
        ii. Once we have the estimated true values, we can generate reserve prices similar to how we did in second-price auctions (revenue equivalence theory), basically assuming bidders bump up their bids to reserve price as long as the reserve price does not exceed their true value.

Model Design - Value Estimation from [redacted]'s slides

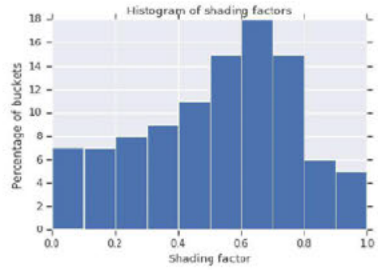
If buyers bid to optimize expected utility, we can reverse-engineer the original value:

- Buyer solves $\max_b (v - b) \cdot F(b)$, leads to $v = b^* + F(b^*) / f(b^*)$.
- Under simplifying assumptions, shading is linear: $b^* = \alpha(F) \cdot v$.
- Obtain a shading factor for each **buyer** and **inventory bucket**.

Using estimated shading factors, we can then optimize reserves:

- Assume buyers bump up their bid to meet reserve when needed.
- Scan for optimal reserve in each inventory bucket.

Flume pipeline implemented to estimate shading factors and optimal reserves.



Model Design - DynamicPriceKey

1. Country
2. Web_property
3. Adslot_code
4. [Maybe] cookie_presence.
5. ...

Experiment Design

1. Traditional traffic-split experiments can only measure the short-term effect (floor-aware bidding), cannot measure long-term effect (changes in bidders' bidding models). Hence it's likely to show revenue drop.
2. In order to measure long-term revenue impact, we can do either of the following:
    a. [redacted]
    b.

Current status - Web

We are evaluating 4 models: quantile model, true value estimation model, quantile model with cookie_presence signal, true value estimation model with cookie_presence signal.

Current status - Web

[redacted]

Current status - App

- Tried both true-value estimation based on model and quantile based model. Current model is quantile based model.
    - Only treating single-call adslots.
- Negative revenue/payout so far (experiment link).
    - RTB is positive.
- TODOs
    - Try cookie_presence signal.
    - Analyze the experiments by breaking down adslots with high/low/no pub floors.
    - Add custom DBM model.

References

1. UBC game theory course.
2. Auction Theory, Vijay Krishna, 2009 (Google Book link).
3. First-Price RPO | Auction Brown Bag
4. First Price RPO Lightning Talk
5. Value estimation for first-price traffic
6. Setting Optimal Reserve Using Value Estimation